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PAPER

Enhancing University English Teaching through Mobile Interactive Applications from an Educational Technology Perspective

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ABSTRACT

In the context of globalization and rapid advancements in information technology (IT), the application of educational technology in higher education has become increasingly prevalent. Particularly in university English teaching, mobile interactive applications have emerged as a significant teaching model. These applications transcend the constraints of time and space, providing students with a flexible learning environment that promotes interaction between teachers and students, thereby enhancing learning outcomes. However, existing research has primarily focused on the technological development and effectiveness evaluation of mobile interactive applications, neglecting the impact of student interaction and trust on learning outcomes. Additionally, there is a lack of dynamism and personalization in the recommendation of educational resources and study partners. This study constructs global and local dynamic trust models for mobile interactions, calculates trustworthiness based on mobile interactive behaviors, and integrates mobile interaction trust relationships and behaviors with a dynamic English recommendation algorithm, thereby providing a new theoretical framework and a practical approach for university English teaching, aiming to enhance the teaching effectiveness and improve students' learning experiences.

KEYWORDS

mobile interactive applications, university English teaching, dynamic trust model, trustworthiness calculation, dynamic recommendation algorithm

1 INTRODUCTION

In the context of globalization and rapid advancements in information technology (IT), the application of educational technology in higher education has become increasingly widespread and profound [1–4]. Particularly in university English teaching, traditional classroom teaching methods are gradually being replaced by mobile interactive teaching models [5, 6]. The emergence of mobile

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interactive applications has not only enriched teaching methods and content but has also provided students with opportunities for learning and interaction anytime and anywhere. This teaching model, through the use of mobile devices and Internet technology, promotes interaction between teachers and students, as well as among students, which helps to enhance students' learning interests and outcomes [7–11]. However, effectively utilizing mobile interactive applications to improve the quality of university English teaching remains a topic worthy of in-depth research.

The application of mobile interactive applications in university English teaching is of significant research importance. Firstly, they transcend the limitations of time and space, providing students with a flexible learning environment that meets the needs of personalized learning [12–15]. Secondly, through mobile interactive applications, teachers can understand students' learning dynamics and feedback in real time, allowing for timely adjustments to teaching strategies, thereby improving the specificity and effectiveness of teaching [16, 17]. Additionally, mobile interactive applications can foster collaborative learning among students, enhancing the fun and interactivity of learning and cultivating students' autonomous learning abilities and team spirit. Therefore, research on the application of mobile interactive applications in university English teaching has both theoretical significance and practical value.

While many studies have examined mobile interactive applications in education, they often have shortcomings. Most research concentrates on the technology's development rather than assessing and optimizing its effectiveness in particular teaching contexts. Additionally, existing studies typically analyze individual learning behaviors without considering how student interaction and trust affect learning outcomes [18, 19]. Additionally, current methods for recommending educational resources and study partners lack dynamism and personalization, making it difficult to meet the diverse learning needs of different students [20]. Hence, it is necessary to construct more comprehensive and dynamic models to enhance the effectiveness of mobile interactive teaching.

This study consists of three main parts. Firstly, global and local dynamic trust models for mobile interactions were constructed. By analyzing students' behaviors and interactions during mobile interactions, their global and local trustworthiness were evaluated. Secondly, trustworthiness was calculated based on mobile interactive behaviors, exploring the impact of different interactive behaviors on trustworthiness and proposing corresponding calculation methods. Finally, a dynamic English recommendation algorithm that integrates mobile interaction trust relationships and behaviors was proposed, providing personalized learning resources and study partner recommendations for students. This study not only enriches the theoretical study of mobile interactive teaching but also offers new perspectives and methods for the practice of university English teaching, holding significant theoretical and practical value.

2 CONSTRUCTION OF GLOBAL AND LOCAL DYNAMIC TRUST MODELS FOR MOBILE INTERACTIONS

In mobile interactive teaching activities, the construction of global and local dynamic trust models is an essential method for enhancing teaching effectiveness and student engagement. The global trust model is primarily calculated based on students' behaviors and reputation values within the entire mobile learning community. This includes students' participation in different course modules, timeliness in submitting assignments, activity levels in discussion forums, and their contributions in assisting and collaborating with other students. This model does not rely on direct interaction information between students but forms a global evaluation of each student through extensive data collection and analysis. In contrast, the local trust model focuses on direct interactions between students. For instance, in scenarios such as group discussions, collaborative projects, or one-on-one tutoring, the system can record the frequency of interactions, the quality of interaction content, and mutual evaluations. When students exhibit good interaction records and high-quality cooperation, their local trust values increase accordingly, and vice versa.

When constructing the global dynamic trust model for mobile interactions, the characteristics of the mobile interaction network in teaching activities should be fully considered. The global trust model mainly relies on students' interaction behaviors and social relationships. By analyzing these behaviors and relationships, students' reputations and influences within the network were evaluated. Firstly, various interaction data on the mobile interaction platform was collected and analyzed, including discussion forum posts, resource sharing, assignment submissions and reviews, online quiz scores, and the frequency and quality of interactions with other students. Based on the interaction data among students, a mobile interaction network graph was constructed. Graph algorithms were utilized to evaluate each student's reputation value within the mobile interaction network. By integrating students' reputation values and their positions within the mobile interaction network, each student's global trustworthiness was calculated. Assuming that the weight of student t in the mobile interaction network graph is represented by TR^{GL}, the in-degree of student i in the mobile interaction network graph is represented by $INT(i)$, the maximum in-degree in the mobile interaction network is represented by $MAX(IN(T))$, and the minimum in-degree is represented by $MIN(IN(T))$, the calculation formula is given as follows:

$$TR^{GL} = \frac{MAX(IN(T)) - IN(i)}{MAX(IN(T)) - MIN(IN(T))} \tag{1}$$

The focus of constructing the local dynamic trust model for mobile interactions lies in capturing and quantifying the direct trust relationships between students, which are particularly crucial in mobile interactive teaching activities. Figure 1 illustrates the sources of trust selection in local mobile interactive dynamic trust. The local trust model emphasizes the trustworthiness between students and their direct contacts, providing the foundation for personalized interaction and collaboration. The model transforms students' interactive behaviors on the platform into a trust relationship graph. In this graph, nodes represent students, and edges represent the direct trust relationships between them. If frequent interactions, such as private chats and high mutual evaluations of assignments, occur between two students, an edge is established between them. Considering the proximity and different preferences among friends, the edge weights can be further adjusted. By analyzing the frequency, quality, and types of interactions, different weights were assigned. Since indirect trust in the local trust model is implicit, it needs to be inferred through direct trust relationships. Methods such as transitive closure or path analysis can be employed to deduce indirect trust relationships. Assuming that the indirect trust value between student i and student n, obtained through trust transference, is represented by TR^{IN}, the trustworthiness of student i in student y by S_{iy}, the trustworthiness of student y in student n by S_{yn}, and the set of neighbors of student i by $V(i)$, the formula for indirect trust value is given as follows:

$$TR^{IN} = \frac{\sum_{j \in V(i)} S_{iy} S_{yn}}{\sum_{j \in V(i)} S_{iy}} \tag{2}$$

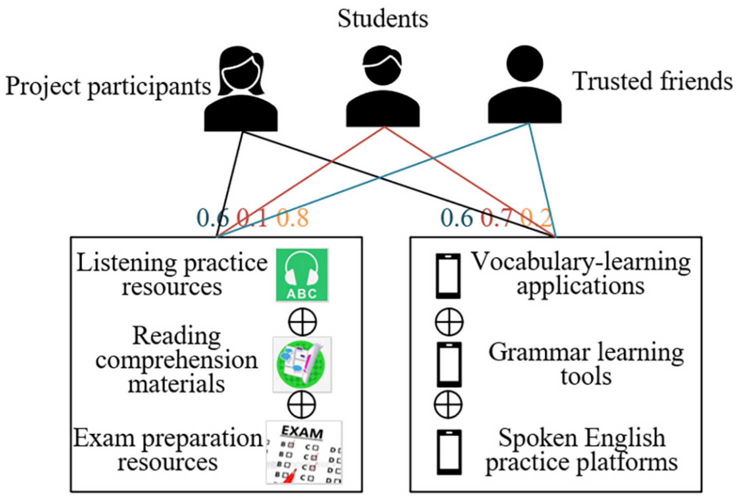


Fig. 1. Sources of trust selection in local mobile interactive dynamic trust

Assuming that the shortest path between student i and student n is represented by f, i.e., the shortest distance to reach student n from student i through trust propagation, the calculation method for local trust is as follows:

$$TR^{LO} = \frac{1}{f} \cdot TR(i,n)^{IN} \tag{3}$$

In mobile interactive teaching activities, trust relationships between students are dynamically changing. These changes are influenced not only by the frequency and quality of interactive behaviors but also by the time factor. To construct a more accurate trust model, the decay characteristics of trust relationships over time should be considered. It can be understood that earlier interactive behaviors should have a gradually diminishing impact on the current trust level, while recent interactive behaviors should carry more weight. Assuming the time weight of interactions between students is represented by S, the most recent interaction time between student i and student u is represented by s'_{iu}, the g-th interaction between the two students is represented by s^g_{iu}, and the time decay factor is represented by λ, the calculation method for the time decay function is as follows:

$$S = e^{-\frac{\left(s'_{iu} - s^g_{iu}\right)}{\lambda}} \tag{4}$$

If the decay of trust over time is considered for local trust, the calculation method is as follows:

$$TR^{LO-S} = \frac{1}{f} \cdot TR(i,n)^{IN} \cdot S \tag{5}$$

For global trust, considering the decay of trust over time, the calculation method is as follows:

$$TR^{GL-S} = \frac{MAX(IN(T)) - IN(i)}{MAX(IN(T)) - MIN(IN(T))} \cdot S \tag{6}$$

Assuming that the comprehensive trust value considering the time decay characteristics is represented by $TR(i,n)^{CO}$, global trust without considering local trust is represented by $TR^{GL\text{-}S}$, and local trust without considering global trust is represented by $TR^{LO\text{-}S}$. By adjusting the proportion of global trust and local trust in the trust relationship using the weight factor β, the calculation methods are as follows:

$$TR(i,n)^{CO} = \beta TR(i,n)^{GL-S} + (1-\beta)TR(i,n)^{LO-S} \tag{7}$$

$$TR(i,n)^{CO} = \begin{cases} TR^{GL-S} \\ \beta TR^{GL-S} + (1-\beta)TR^{LO-S} \\ TR^{LO-S} \end{cases} \tag{8}$$

3 TRUSTWORTHINESS CALCULATION BASED ON MOBILE INTERACTIVE BEHAVIORS

In mobile interactive teaching activities, students' interactive behaviors not only affect their learning experience and outcomes but also have a profound impact on subsequent collaboration and trust relationships. The calculation method for trustworthiness based on user behavior is crucial in this context. To ensure that the trustworthiness calculation is accurate and effectively eliminates false information, a dynamic trust model that comprehensively considers the quality, frequency, and temporal factors of interactive behaviors should be established.

The uniqueness of mobile interactive teaching activities lies in the variety of student interactions, which include ratings and reviews, questions and answers, resource sharing, and collaborative tasks. Therefore, evaluating the reliability of these behaviors is essential for calculating trustworthiness. In mobile interactive teaching activities, when students rate an interaction, the reliability of the rating depends on the consistency and objectivity of the student's ratings. If a student's rating aligns with the trend of most students' ratings or closely matches the overall evaluation trend, it indicates that the rating is objective and reliable. In other words, the closer the rating is to the overall average level, the higher its reliability. In this study, the principle of calculating the reliability of rating information ensures that students' ratings and interactive behaviors in mobile interactive teaching activities accurately reflect their trustworthiness and contribution. This study employs the trustworthiness between students as a measure and defines the reliability of rating information through a linear combination of two key functions: co-student similarity and co-project similarity. Co-student similarity refers to the intersection count of similar students between student i and student n, based on the count of similar students in student i. In mobile interactive teaching activities, this means that if two students exhibit similar patterns in their interactions with other students, their trustworthiness increases. Co-project similarity refers to the intersection count of evaluated projects between student i and student n, based on the count of their evaluated projects. In mobile interactive teaching activities, this means that if two students rate the same learning resources and their ratings are highly consistent, their trustworthiness will also increase accordingly. Assuming that the sets of similar students for student i and student n are represented by H_i^T and H_n^T, respectively, and the count of common similar students between student i and student n is represented by $H_i^T \cap H_n^T$, the calculation method for co-user similarity is:

$$ZIT(i,n) = \frac{\left|H_i^T \cap H_n^T\right|}{\left|H_i^T\right|} \tag{9}$$

Assuming that the sets of rated items for students i and n are represented by L_i^E and L_n^E, respectively, and the count of common rated items between student i and student n is represented by $L_i^E \cap L_n^E$, the calculation method for co-project similarity is as follows:

$$ZUT(i,n) = \frac{\left|L_i^E \cap L_n^E\right|}{\left|L_i^E\right|} \tag{10}$$

By linearly combining the functions of co-student similarity and co-project similarity, a more comprehensive evaluation of the trustworthiness between students and the reliability of rating information can be achieved. The reliability calculation formula between two students is given as follows:

$$RE(i,n) = \frac{ZIT(i,n) + ZUT(i,n)}{2} \tag{11}$$

In the study of trustworthiness calculation based on mobile interactive behaviors, the consistency of rating information is also a crucial indicator to ensure that students' evaluations of mobile interactive teaching activities accurately reflect their cognition and experience. By introducing the consistency of rating information, it becomes possible to effectively identify and filter out inconsistent or false ratings, thereby improving the quality and trustworthiness of ratings in mobile interactive teaching activities. The consistency of rating information can be measured in two ways: a) whether students maintain stable ratings across different learning resources; and b) the consistency of student ratings is also reflected in the deviation between student ratings and overall reputation. Based on reputation calculation, the objectivity $P(e)$ of ratings can be determined by comparing students' ratings with the comprehensive reputation of the evaluated items. The standard deviation C_v is used to measure the variation in this comparison. When the deviation between student ratings and the comprehensive reputation of items is small, the ratings are considered objective, and the consistency of rating behaviors is high. The specific calculation method is as follows:

$$P(e) = \left|\frac{e - \bar{e}_v}{C_v}\right| \tag{12}$$

The calculation formula for the objective activity $P(i)$ of student ratings is as follows:

$$P(i) = \frac{1}{\left|E_i\right|} \sum_{e \in E_i} P(e) \tag{13}$$

The specific calculation method for the consistency $Z(i)$ of students is as follows:

$$Z(i) = \frac{1}{\left|E_i\right|} \sum_{e \in E_i} (P(e) - P(i))^2 \tag{14}$$

The trustworthiness of students' mobile interactive behaviors is calculated as follows:

$$CR(i,n) = \frac{RE(i,n)Z(i)}{2} \tag{15}$$

By integrating the time-decayed trustworthiness with the trustworthiness between students' mobile interactive behaviors, the final dynamic trustworthiness calculation formula is as follows:

$$TS(i,n)^{DY} = \eta CR(i,n) + (1-\eta)TR(i,n)^{CO} \tag{16}$$

4 DYNAMIC ALGORITHM FOR ENGLISH TEACHING RECOMMENDATIONS BASED ON MOBILE INTERACTION TRUST AND BEHAVIOR

In mobile interaction networks, students prioritize peer opinions over ratings when choosing learning resources, focusing on trusted peers. The algorithm utilizes global and local trust to identify trusted neighbors and filters reviews to separate genuine from false students, ensuring reliable evaluations. The algorithm's schematic representation can be seen in Figure 2.

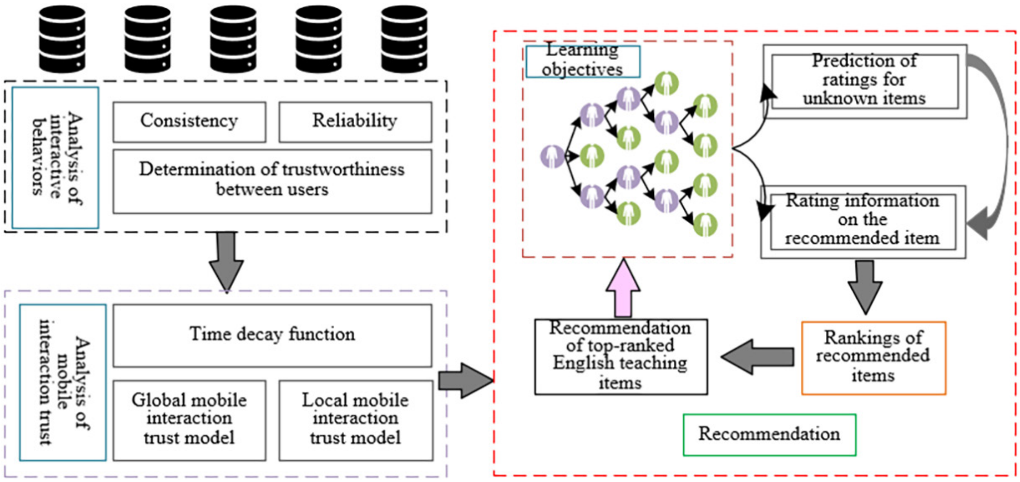


Fig. 2. Diagram of the dynamic English teaching recommendation algorithm

First, the algorithm calculates trustworthiness by considering time decay, using global trust from students' overall reputations and local trust from direct interactions. This ensures trust values remain current and dynamic. Then the algorithm analyzes specific interactive behaviors in mobile interactive teaching activities, including the use of learning resources, course participation, and timeliness of feedback. Through this behavioral data, the algorithm further evaluates the consistency and reliability of student reviews, thus calculating the trustworthiness of student behavior. On this basis, the algorithm integrates comprehensive trustworthiness with the trustworthiness of student behavior, setting recommendation weight parameters. This integration process ensures that the recommendation system comprehensively considers trust relationships and specific student behaviors to generate more accurate and reliable rating prediction results. In this way, the algorithm not only improves the accuracy of recommendations and student satisfaction but also enhances students' trust in the recommendation system. Assuming that the integrated dynamic recommendation trustworthiness is represented by $TR(i,n)^{DY}$, the trustworthiness of student behavior by $CR(i,n)$, and the comprehensive trustworthiness after time decay by $TR(i,n)^{CO}$. When there is no trust relationship between students, $CR(i,n)$ is used as the dynamic recommendation trustworthiness. When there is no interactive behavior between two students, $TR(i,n)^{CO}$ is used to represent the dynamic recommendation trustworthiness. Then there are piecewise functions as follows:

$$TR(i,n)^{DY} = \begin{cases} TR(i,n)^{CO} \\ \eta CR(i,n) + (1-\eta)TR(i,n)^{CO} \\ CR(i,n) \end{cases} \tag{17}$$

Assuming that the average rating of student i for all recommended items is represented by $\bar{E}_i$, the average rating of student n for all items is represented by $\bar{E}_n$, the set of the target student's neighbors is represented by V, and the dynamic trustworthiness of student i towards student n is represented by $TR(i,n)^{DY}$, the predicted rating of the target student for an item is represented by $\hat{E}_{nu}$. The rating prediction result can be obtained by combining comprehensive trustworthiness and the trustworthiness of students' mobile interactive behaviors based on the following formula:

$$\hat{E}_{nu} = \bar{E}_i + \frac{\sum_{n \in V} TR(i,n)^{DY}(E_{nu} - \hat{E}_n)}{\sum_{n \in V} TR(i,n)^{DY}} \tag{18}$$

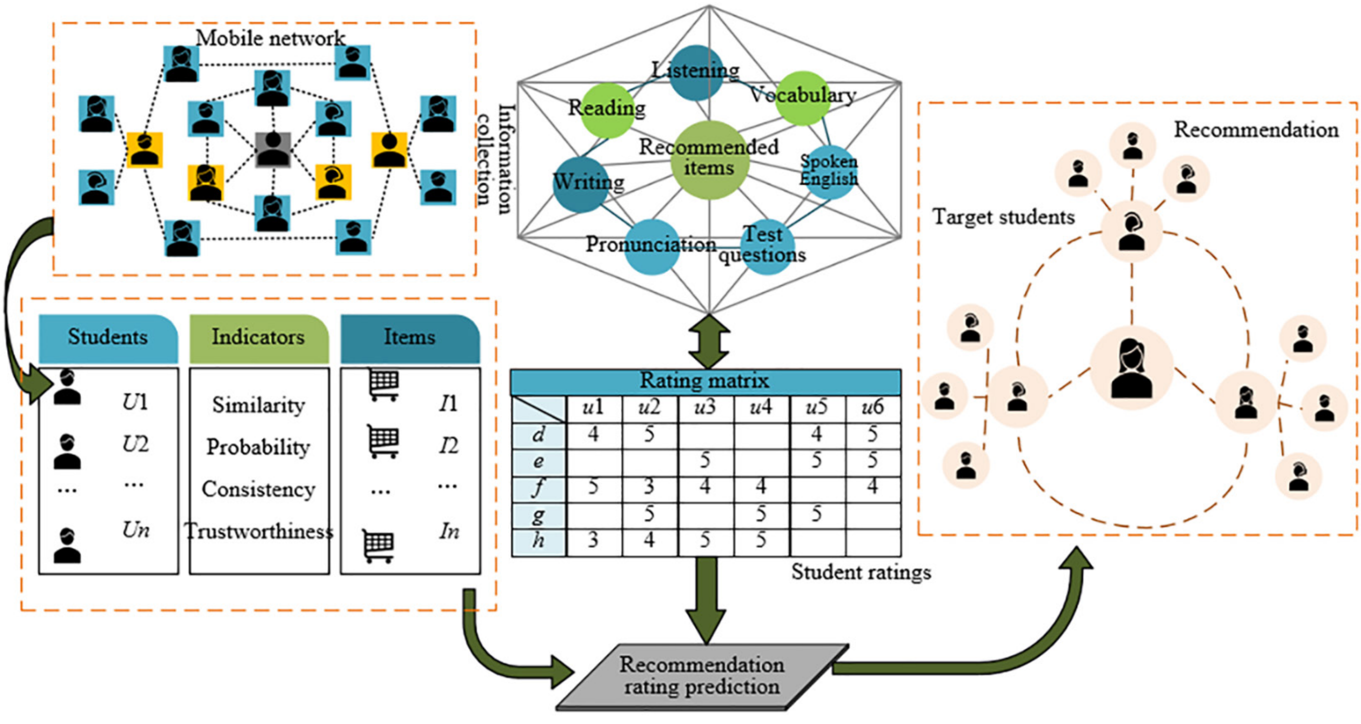


Fig. 3. Process flow of the proposed dynamic English teaching recommendation algorithm

Figure 3 demonstrates the process of the proposed dynamic English teaching recommendation algorithm. The specific steps of the algorithm are as follows:

Step 1: First, the presence of a social relationship between student i and student n in the mobile interaction network was checked. If such a relationship exists, global trust and local trust between them can be calculated. Global trust is based on the students' reputations across the entire network, evaluating their long-term reliability. Local trust is based on direct interaction records between students evaluating their trustworthiness in specific relationships.

Step 2: The comprehensive trustworthiness after time decay was calculated. Since students' trust relationships change over time, the trust values need to be adjusted through a time decay function to reflect the current trust level.

Step 3: The presence of interaction behaviors and information sharing between student i and student n was determined. If they are present, a detailed analysis of the students' interactions in mobile interactive teaching activities is conducted, including the use of learning resources, course participation, and timeliness of feedback.

Step 4: Based on the students' rating information, the consistency of the students was analyzed. Consistency reflects the stability and uniformity of a student's ratings, indicating whether the student maintains a high level of consistency in their ratings across different times and resources.

Step 5: Similarly, the reliability of the students based on their rating information was analyzed. The reliability of a student assesses the credibility of their ratings, determining whether their ratings align with those of other students and whether there are any significant deviations.

Step 6: Using the consistency and reliability obtained in Steps 4 and 5, the trustworthiness between student i and student n was calculated. This trustworthiness combines the consistency and reliability of student ratings, providing an overall assessment of the students' rating behavior.

Step 7: The comprehensive trustworthiness calculated in Step 2 was integrated with the trustworthiness of student behavior information to form a dynamic trustworthiness. Dynamic trustworthiness combines the trust relationships of students in the mobile interaction network with their specific interactive behaviors, providing a dynamic and timely trust evaluation.

Step 8: If no common student interaction behaviors exist between student i and student n, the comprehensive trustworthiness should be used as the dynamic trustworthiness. In this case, the prediction ratings rely mainly on global and local trust relationships.

Step 9: If no social relationship exists between student i and student n, only the trustworthiness of student behavior information should be used as the dynamic trustworthiness. In this scenario, the prediction ratings rely primarily on the specific behavior data of students in mobile interactive teaching activities.

Step 10: Finally, the obtained dynamic trustworthiness was used to predict the ratings of unknown items through the rating prediction formula. The formula combines trustworthiness and behavior data to generate a rating prediction for the target student. Based on the predicted ratings, the items were ranked to create a recommendation list.

5 EXPERIMENTAL RESULTS AND ANALYSIS

It can be observed from the data in Figure 4 that the recall exhibits a certain variation trend with changes in the comprehensive trust parameter in both the training set and the test set. In the training set, as the comprehensive trust parameter increases from 0 to 1, the recall rises from 0.06 to 0.072 and then gradually declines to 0.062. This indicates that a moderately comprehensive trust parameter (e.g., 0.2) can better improve the recall in the training set. In the test set, the recall shows a similar trend with changes in the comprehensive trust parameter. It rises from 0.069 to 0.082 and then declines, reaching a minimum of 0.064. This demonstrates that the comprehensive trust parameter has a significant impact on the recall, and the optimal parameter value in the test set is consistent with that in the training set, both achieving the highest recall at around 0.2. Data analysis suggests that a moderately comprehensive trust parameter helps improve recall, whereas excessively high or low values lead to a decline in recall. This occurs because a moderate trust parameter can more effectively balance global and local trust information, thereby better capturing users' actual interactive behaviors and trust relationships. In both the training set and the test set, the comprehensive trust parameter of 0.2 results in the highest recalls of 0.072 and 0.082, respectively. This indicates that the proposed dynamic English teaching recommendation algorithm performs best at this parameter value, providing students with more personalized learning resources and study partner recommendations.

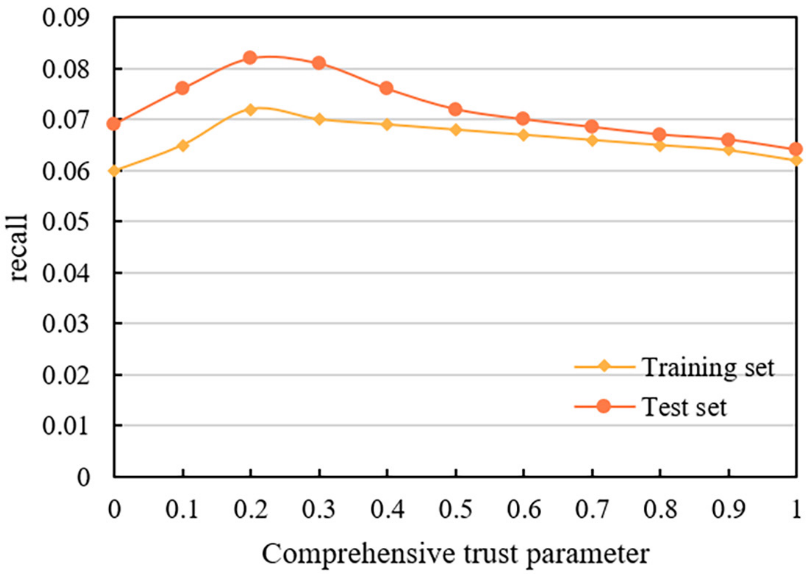


Fig. 4. Impact of the comprehensive trust parameter on the proposed method in recall

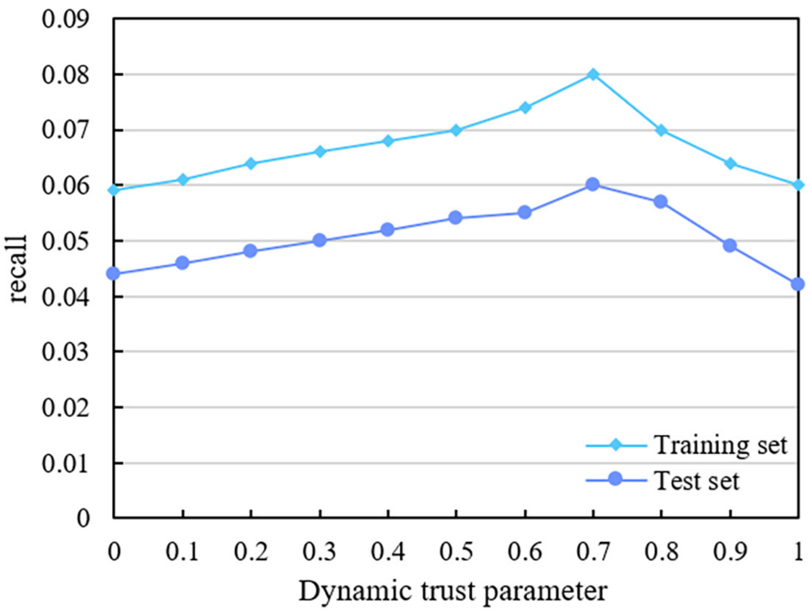


Fig. 5. Impact of the dynamic trust parameter on the proposed method in recall

It is evident from the data in Figure 5 that the recall in both the training set and the test set exhibits a clear trend with changes in the dynamic trust parameter. In the training set, as the dynamic trust parameter increases from 0 to 1, the recall rises from 0.059 to 0.08 and then begins to decline, ultimately reaching 0.06 at 1. This trend indicates that moderate to high dynamic trust parameters can significantly improve the recall in the training set, particularly at a parameter value of 0.7, where the highest value is achieved. In the test set, the recall similarly increases from 0.044 to 0.06 with an increase in the dynamic trust parameter and then begins to decline, reaching 0.042 at 1. The test set shows a similar trend, with the highest recall also occurring at a dynamic trust parameter of 0.7. Analysis of the data suggests that moderate to high dynamic trust parameters help improve the recall, particularly at a parameter value of 0.7, where both the training set and the test set achieve the highest recalls. This finding indicates that the proposed dynamic English teaching recommendation algorithm can more effectively capture students' interactive behaviors and trust relationships at a dynamic trust parameter of 0.7, thereby providing more accurate personalized learning resources and study partner recommendations. Excessively low or high dynamic trust parameters result in the model's inability to comprehensively or adequately capture interactive behaviors and trust relationships, leading to a decrease in recall. Therefore, in practical applications, a dynamic trust parameter of around 0.7 should be selected to maximize the performance and effectiveness of the recommendation system.

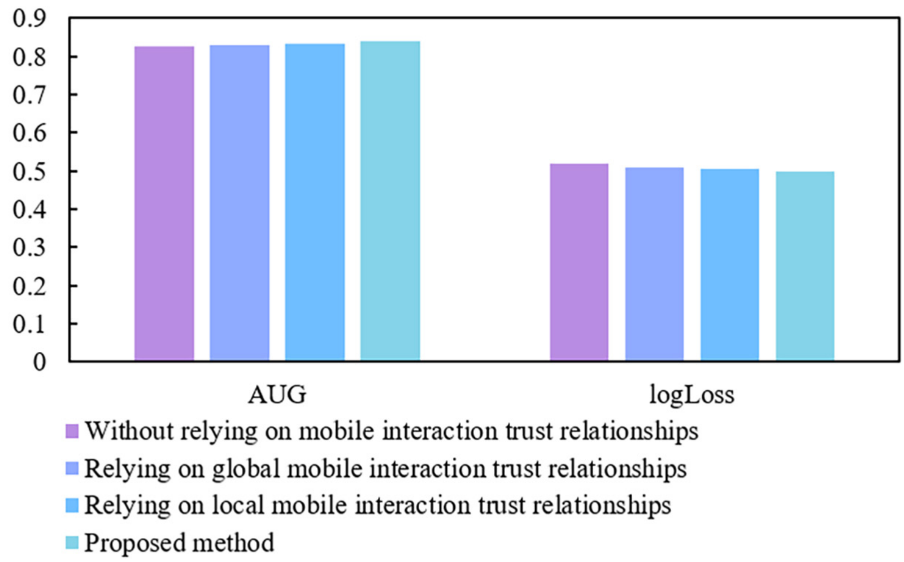
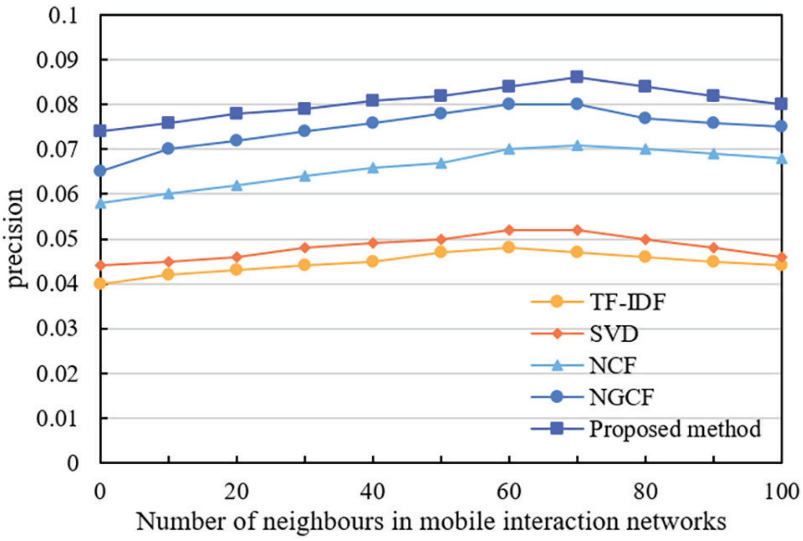
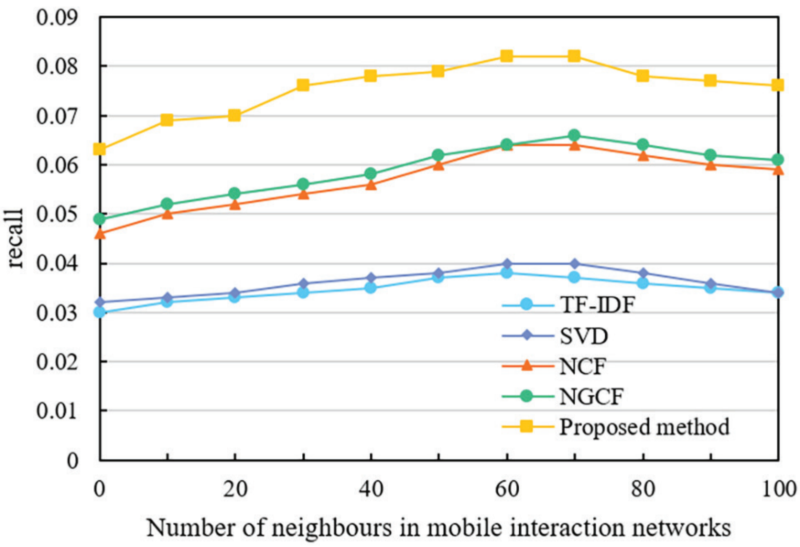


Fig. 6. Results of the ablation experiment

It is evident from the data in Figure 6 that the proposed method outperforms other methods in the ablation experiment. Without relying on mobile interaction trust relationships, the average utility gain (AUG) is 0.825 and the log loss is 0.52. When relying on global mobile interaction trust relationships, the AUG increases to 0.83 and the log loss decreases to 0.51. Further reliance on local mobile interaction trust relationships results in an AUG of 0.835 and a log loss of 0.505. Finally, the proposed method, which integrates both global and local mobile interaction trust relationships, achieves the highest AUG of 0.84 and the lowest log loss of 0.5. These results indicate that the performance of the system improves with each additional trust model dependency. Analysis of the ablation experiment results shows that mobile interaction trust relationships significantly impact the performance of the recommendation system. Specifically, models that rely on both global and local trust relationships outperform those that use only a single trust relationship or none at all in terms of both AUG and log loss. This validates the effectiveness of the proposed dynamic English teaching recommendation algorithm, which, by integrating global and local mobile interaction trust relationships, captures students' interactive behaviors and trust relationships more comprehensively, thereby enhancing the performance of the recommendation system.



a) Accuracy



b) Recall

Fig. 7. Recommendation performance comparison of different methods with varying numbers of neighbors in mobile interaction networks

It is evident from the data in Figure 7 that the proposed method consistently outperforms other methods in terms of recommendation performance across different numbers of neighbors in the mobile interaction network. Regarding accuracy, the proposed method increases from 0.074 with 0 neighbors to 0.086 with

80 neighbors, then slightly decreases but remains above 0.082. In terms of recall, the method increases from 0.063 with 0 neighbors to 0.082 with 80 neighbors, then slightly decreases but stays above 0.076. In comparison, other methods such as term frequency-inverse document frequency (TF-IDF), singular value decomposition (SVD), neural collaborative filtering (NCF), and neural graph collaborative filtering (NGCF) also show improvements in accuracy and recall as the number of neighbors increases, but their overall performance remains lower than that of the proposed method. Additionally, these methods show a decline in performance once the number of neighbors exceeds a certain value (typically around 80). Analysis of the recommendation performance across different numbers of neighbors in the mobile interaction network indicates that the number of neighbors significantly affects the system's performance. Both accuracy and recall of the proposed method continuously improve as the number of neighbors increases, reaching optimal values at 80 neighbors before slightly declining but still maintaining a high level. This suggests that moderately increasing the number of neighbors in the mobile interaction network effectively enhances recommendation performance, whereas an excessive number of neighbors leads to a decline in recommendation effectiveness. In contrast, other methods show limited improvements with increasing neighbor numbers and overall inferior performance compared to the proposed method. This validates the effectiveness of the dynamic English teaching recommendation algorithm, which integrates global and local mobile interaction trust relationships. The algorithm better captures students' interactive behaviors and trust relationships, providing more accurate and effective recommendations across various neighbor configurations.

6 CONCLUSION

This study explored the construction of global and local dynamic trust models for mobile interactions and assessed global and local trustworthiness by analyzing students' behaviors and interactions in mobile interactive processes. Based on this, a dynamic English recommendation algorithm was proposed, aiming to provide students with personalized learning resources and study partner recommendations. Experimental results demonstrated that the proposed method exhibits excellent recalls under different trust parameter settings and consistently outperforms other methods in recommendation performance across various numbers of neighbors in the mobile interaction network. Additionally, the proposed method showed significant superiority in metrics such as AUC, log loss, and NDCG, particularly excelling in accurately distinguishing between positive and negative samples and in the quality of recommendation ranking.

The value of this study lies in proposing a new dynamic recommendation algorithm by integrating global and local mobile interaction trust relationships, thereby better capturing students' interactive behaviors and trust relationships to provide more accurate and effective personalized recommendations. This approach not only enriches the theoretical understanding of trust model construction in recommendation systems but also demonstrates high recommendation performance in practical applications. However, this study has certain limitations. For instance, the model may face issues related to computational complexity and resource consumption when handling large-scale datasets. Moreover, the method primarily focuses on students' interactive behaviors and trust relationships without fully considering other potential influencing factors such as emotional states and learning interests. Future research directions may include further optimizing the computational efficiency of the model, incorporating more dimensions of data to enhance the comprehensiveness and accuracy of recommendations, and conducting more validations and improvements in practical application scenarios. These efforts are expected to further enhance the performance and application value of dynamic recommendation systems.

7 ACKNOWLEDGEMENT

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